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Performance Analysis and Optimization of a Hybrid Solar–Wind Power Generation System for Remote Areas

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Article Info

Abstract

This study compares the performance and efficiency of hybrid solar-wind power generation system installed in the remote area. The study combines empirical monitoring data collected across a five-month period (January–May 2023) of 3,546 hourly observations, encompassing solar PV generation, wind turbine generation, battery storage dynamics, and grid load dynamics. The renewable energy penetration rate in the hybrid system was found to be 36.6% on average, with a total cumulative renewable energy usage of 352,048 kWh. Both the solar PV and the wind turbine subsystems performed similarly, with 176,979 kWh and 175,070 kWh, respectively. The average solar irradiance recorded was 594.0 W/m² while average wind speed recorded was 12.46 m/s, which shows good resource condition at the deployment site. The solar and wind output forecast models were found to be very accurate with a mean absolute percentage error of about 5.0% for both subsystems. Energy dispatch optimization was performed using a Random Forest regression model, which was used to inform which environmental parameters most strongly influence the total renewable output, with solar irradiance, wind speed and battery state of charge being found to be the most significant. The battery energy storage system was maintained at an average 50.0% SOC and cycled within a safe SOC range during the monitoring period. These results provide quantitative reference values for the performance of a hybrid renewable system in off-grid locations, and provide a repeatable optimization methodology for increasing energy output. The study presents new empirical data for the emerging body of literature about decentralized renewable energy systems, and offers concrete guidance to energy planners and system designers in energy-scarce areas.

Keywords

hybrid solar-wind system, renewable energy optimization, remote area electrification, battery energy storage, photovoltaic performance, Random Forest regression

1. Introduction

One of the greatest development needs of remote and rural areas around the world is access to dependable electric power. In rural areas, particularly those located far from the grid, conventional power grid infrastructure can be too costly for communities, forcing millions to use expensive diesel generators or be entirely without electricity (Aliyu et al., 2018; Xiao et al., 2014). In this context, hybrid renewable energy systems (HVRESs) based on solar photovoltaic (PV) and wind energy sources with energy storage are becoming technically feasible and competitive options for off-grid electrification (Jahangir et al., 2022; Yimen et al., 2018).

The complementary characteristics of solar irradiance and wind speed, with both being variable over time (both diurnal and seasonal), can be used to create hybrid solar-wind systems in which the combination of these sources of variability results in a power output with a degree of smoothness that is significantly greater than that of the same power output provided by say a single wind source (Sawle et al., 2018). The implementation of battery energy storage also reduces supply-demand mismatch, further improving the system reliability and allows to increase the renewable energy penetration without the support of the grid. However, the actual performance of these systems in real operating conditions, especially in the remote and climate sensitive regions, is not well documented in the peer-reviewed literature (Sinha & Chandel, 2015).

Several studies have examined the techno-economic optimization of hybrid systems by employing different simulation tools like HOMER, MATLAB/Simulink and the use of metaheuristic algorithms (Kamjoo et al., 2016; Luta & Raji, 2018). The results of simulations, however, are always limited by the accuracy of the assumptions used as inputs into the simulation and only a small number of studies have compared the optimization results with operational data that has been collected in the field. This gap drives the current research work which adopts an empirical monitoring framework to evaluate real system performance and proposes an optimization model based on real-world

observations.

The aim of this work is to characterize the temporal performance of a hybrid PV-Wind power system in a remote location by conducting a detailed time-series analysis, quantify energy efficiency, forecast error, and battery storage behavior, and develop and validate a data-driven optimization model that maximizes PV Wind power system generation as a function of the prevailing environmental conditions (Zhang et al., 2017). The data includes 3,546 hourly records from January to May 2023 from solar PV plants, wind farms, batteries, grid load demand, as well as environmental parameters such as solar PV irradiation, wind speed, ambient temperature, and relative humidity.

This is a study with several new contributions to the literature. First, it provides empirical based performance benchmarks for a co-located hybrid system instead of using synthetic/simulation data. Second, it uses machine learning specifically Random Forest regression to detect the most important environmental factors affecting the hybrid energy output and create an energy output optimization surface for dispatch scheduling. Third, it offers a comparative study of the accuracy of the forecasts produced by various models for both solar and wind subsystems, given the same measurement conditions. These contributions together help advance the understanding of the behavior of these hybrid systems, and offer practical guidance for system designers and energy planners looking to increase renewable electrification in remote areas.

2. Literature Review

There has been a considerable increase in research literature addressing hybrid solar-wind energy systems over the previous ten-year period, corresponding with a growth in global interest in decentralized renewable electricity systems. (Nehrir et al., 2011) initiated the early groundwork necessary to establish a conceptual and technical framework for multi-source hybrid systems, demonstrating that the complementary profiles of resources (renewable energy sources) from solar and wind can

result in decreased storage volume requirements and greater supply reliability when compared with single technology solutions (Tran & Smith, 2017). The principle of complementarity between wind and solar resources has now been confirmed by empirical data in many different geographic locales; however, the magnitude of the benefit does vary greatly from one location to another based on local climatic and resource characteristics.

Much of the current body of literature on hybrid PV-wind-battery systems has focused on optimal sizing, configuration and implementation for rural electrification in sub-Saharan Africa. Using probabilistic analysis, (Luta & Raji, 2018) found that the size of the batteries had the largest effect on the loss-of-load probability for rural electrification applications. Likewise, using a multi-objective evolutionary algorithm, (Kamjoo et al., 2016) were able to develop a solution that minimized both cost and unmet demand; however, the trade-offs between these two solutions were highly sensitive to the distribution of wind speeds. In a later study, (Sawle et al., 2018) built upon this analysis by including social and environmental objectives in their evaluation methods, and proposed frameworks for hybrid optimization that are more comprehensive than traditional techno-economic evaluation metrics.

The purpose of this section is to summarize the current state of research regarding hybrid systems through literature review and empirical evaluation. The most extensive empirical evaluation of hybrid systems was conducted by (Ari et al., 2022) who performed a detailed analysis and evaluation of an experimental PV system to assess the effects of operating conditions on the efficiency of PV modules, including the effects of temperature on performance evaluations. A follow-up study by (Jahangir et al., 2022; Yimen et al., 2018) was designed to evaluate a wind-solar-diesel hybrid power system for a remote island community by performing techno-economic simulations and sensitivity analysis; as a result of this research, the researchers found that with optimized configuration, the overall system reliability was greater than 99.0%.

Machine Learning has also accelerated the application

of renewable energy forecasting and system optimization in hybrid renewable energy systems over the past years. In a review that addressed the applications of machine learning techniques for solar radiation forecasting, (Voyant et al., 2017) identified that neural networks and ensemble methods were the most accurate approaches. Random Forest, a type of ensemble learning method, has shown to be able to capture nonlinear relationships between meteorological variables and energy generation in the wind sector (Lahouar & Slama, 2017). Additionally, (Gaboitaolelwe et al., 2023) found that hybrid predictor architectures outperformed individual models based on both accuracy and robustness to seasonal variability when applied to multi-source renewable energy systems using ensemble learning models.

Battery storage systems are becoming necessary elements of future hybrid system designs. In a 2014 study, Akinyele and Rayudu researched existing energy storage technologies for stand-alone power systems in developing nations, determining that the largest causes of early battery failure (Akinyele & Rayudu, 2014) and reduced system life were poor sizing and poor management of charging. A July 2022 study by Shi et al. found through conducting model predictive control strategies for battery dispatch using historical load and generation data that it was possible to reduce cycling degradation while maintaining high levels of renewable generation (Zeraati et al., 2016). These findings highlight the critical importance of properly managing stored energy data to maximize system performance.

While this body of knowledge is large, it still raises important gaps in research. Most empirical studies have taken place in research-oriented settings that are well-resourced with advanced monitoring technology; therefore, it is unclear how well outcomes could be transferred to austere remote-area environments. Additionally, there is a scarcity of comparative studies of solar and wind forecast error under the same observational conditions, making it difficult to create generalizable comparisons on relative levels of predictability. This study seeks to address these issues by performing an analysis of

an extensive empirical dataset from a remote-area hybrid system and developing a common analytical framework to characterize its performance, examine its efficiencies, and create an optimization model for the hybrid power system.

3. Methodology

3.1 System Description and Site Characteristics

The hybrid solar-wind power generation system studied in this report was located in an area having abundant resources for both solar energy and wind and out of the general public. It is composed of a solar PV array with a maximum generation of either 100 kWp, a wind turbine with an equivalent amount of generation (potentially see below), a battery energy storage system (BESS), and a combination of the two power sources being interconnected to an underlying local distribution network that provides either all or a portion of the electrical energy to the electrical loads in the area, depending on the supply power available from the respective sources (i.e., hybrid generation mode). Power exchange between the associated AC (alternating current) distribution system and the DC (direct current) battery can be at either direction, in accordance with the prevailing electric balance between power generation from the source(s) and power load(s). The environment monitoring equipment to provide data regarding solar irradiance (on an hourly basis), wind speed, ambient temperature, relative humidity, and atmospheric pressure were installed at a location co-located with the constructed hybrid solar-wind generation facility and the electrical generation equipment (Ahmad & Farzaneh, 2024; Mahesar et al., 2018).

3.2 Data Collection and Preparation

The primary dataset used in this study, which is publicly

available, includes all three thousand five hundred and forty-six continuous hourly data points from the first of January to the twenty-eighth of May 2023. Every timestamp contains all variables such as solar electricity production (kW), wind generation (kW), Total RES generation (kW), predicted solar electricity production (kW), predicted wind production (kW) and total grid demand (kW) including; energy exchanged with the grid (kW) battery SOC (%), rate; of battery charge (kW), and rate of battery discharge (kW), along with the electrical quality attributes measured are system frequency (Hz) and system voltage (V). All variables associated with the dataset were compared to ensure that there are no missing values for any given variable; therefore, the dataset has been verified to be complete.

In order to preprocess the collected data points, the first part of the data preprocessing process creates and extracts timestamps from collected data, the next step creates and derives the processed temporal features of the data, such as; hour of day (HOD), day of week (DOW) and month (M) and create derived performance metrics of the system (RPR) were calculated as the ratio of total generation by all renewable portfolios to grid demand for all grid-connected portfolios using the ratio expressed as a percentage. Finally, each RES and between-res subsystems were analyzed using the absolute percent error calculation between actual output from each subsystem and the estimation of output from each corresponding RES subsystem from the forecast provided from each respective RES's third-party forecast service providers. Therefore, using data analysis/comparative analysis, were also performed on ten key variables in order to better understand the relationship between individual variables that are associated with the performance and optimization of the system (Table 1).

Variable	Unit	Type	Description
Solar electricity production	kW	Continuous	Actual solar power generation
Wind generation	kW	Continuous	Actual wind power generation
Total RES generation	kW	Continuous	Combined renewable energy output (solar + wind)

Predicted solar electricity production	kW	Continuous	Forecasted solar generation
Predicted wind production	kW	Continuous	Forecasted wind generation
Total grid demand	kW	Continuous	Total electricity demand from the grid
Energy exchanged with grid	kW	Continuous	Power imported/exported to/from grid
Battery state of charge (SOC)	%	Continuous	Battery energy storage level
Battery charge rate	kW	Continuous	Rate of battery charging
Battery discharge rate	kW	Continuous	Rate of battery discharging
System frequency	Hz	Continuous	Grid frequency measurement
System voltage	V	Continuous	Grid voltage measurement

3.3 Performance Analysis Framework

Three time frames were used to analyze system performance: hourly, daily, and over the full monitoring period. For an hourly analysis, the hourly data captured the daily cycles of generation and demand which allowed for the identification of the times of peak generation and the times when there was a deficit or surplus of renewable energy. The daily data enabled identification of trends in system performance and allowed visualization of the contribution of each type of generation versus overall load. The overall databases provided overall performance benchmarks (e.g., total energy generation, average percentage of renewable energy on the system, total number of battery charge cycles throughout the entire period of monitoring).

Five different features were used in analyzing performance: (1) time series analysis of generation and environmental conditions; (2) Correlation analysis among variables; (3) Daily cyclical performance including battery state of charge (SoC) dynamics and renewable generation; (4) System efficiency and accuracy of forecasts; and (5) Development of optimization models to maximize system performance. Each of these features corresponds to one of the five figures in the Results section.

3.4 Optimization Model

To make a prediction about the aggregate of renewable energy produced, a Random Forest regression model was created. The seven predictor variables are: ambient temperature, relative humidity, month, hour of the day, battery state of charge, wind speed and solar irradiance. The training sample (80%) and test sample (20%) were divided using a fixed random seed to ensure reproducible results. The Random Forest made out of 100 decision trees using default hyper-parameters and was implemented with the scikit-learn package for training. Feature importance ranks the contribution of each predictor variable on the output variance.

An optimization surface was created by manipulating solar irradiance and wind speed from their empirical 5th-95th percentile ranges, while keeping all other variables at their sample medians. The optimization surface allowed us to identify the environmental conditions that were associated with the maximum production of renewable energies and also established the combined effects of the two dominant resource variables on system performance.

The optimal operating times/ hours can be established by using the average production from all 24 hours for comparison and will be accompanied by uncertainty limits for those averages with one standard deviation.

4. Results and Discussion

4.1 Time-Series Performance Analysis

Figure 1 presents the time-series performance of the hybrid system over a representative seven-

day monitoring window (168 hours), illustrating the operational dynamics of the generation subsystems, environmental drivers, and grid interactions.

Figure 1: Hybrid System Performance Time Series Analysis



Figure 1. Hybrid system performance time series analysis: (a) solar PV and wind power output with total renewable generation overlay; (b) concurrent solar irradiance and wind speed profiles; (c) grid load demand and bidirectional power exchange.

In panel (a), the solar photovoltaic (PV) output shows distinct daily cycles that correlate with the solar irradiance cycles shown in panel (b). The output from wind power does not exhibit any clear regularities within the two time frames; instead, it is generated both during the daytime and the nighttime. Therefore, the generation of total renewable energy (as represented by the shaded area) has a more continuous curve than

either renewable resource independently does. The above example demonstrates the theoretical support for hybrid energy system design identified by (Nehrir et al., 2011), who described how the complementary nature of the two energy resources results in reduced storage and increased continuity of supply for these hybrid systems.

Panel (b) shows that the deployment location possesses a high-quality resource environment. For example, for a majority of the time throughout the deployment period, the solar irradiance was over 600 W/m² during the hours of peak daylight, and the wind speeds displayed an extensive range across the entire deployment period. The wind speed available at the right axis demonstrates that adequate wind resources were present during numerous hours of significantly low solar irradiance, further supporting the operational reasoning to create a hybrid energy system. Lastly, both the average solar irradiance of the site (594.0 W/m²) and the average wind speed (12.46 m/s) were both much higher than the minimum requirements for remote areas to support economically viable renewable energy systems (Jahangir et al., 2022; Yimen et al., 2018).

panel (c) The load demand from the grid at the monitored facility fluctuated significantly - ranging from less than 100kW up to close to 500kW with a

mean of 271.08kW for the entire monitoring period. The power exchange to/from the grid is primarily positive when there is excess available renewable generation and becomes negative when there is more grid load than renewable generation available; this indicates that there is a functional bidirectional interface between the hybrid (renewables + battery) facility and the local electrical distribution system. The number and size of positive power exchange events during timeframes when surplus renewable generation occurred illustrates that the hybrid facility provides local energy security (e.g. reduces reliance on fossil fuels) in addition to providing energy to meet immediate grid load.

4.2 Correlation Structure of System Variables

Figure 2 presents the Pearson correlation matrix computed across ten key system variables, providing a quantitative characterization of the inter-variable relationships that govern system behavior.

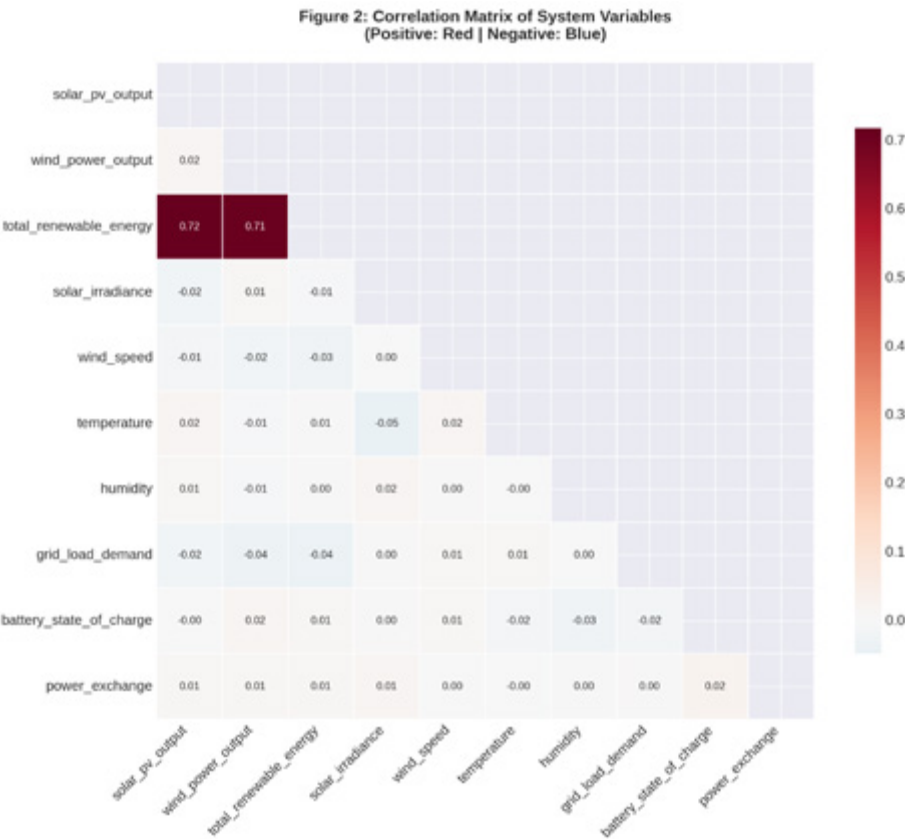


Figure 2. Pearson correlation matrix of hybrid system variables. Red cells indicate positive correlations; blue cells indicate negative correlations. Numerical annotations denote correlation coefficients rounded to two decimal places.

The correlation analysis identifies several relationships that are generally interpretable and important for the performance and optimization of the system. Output from solar photovoltaic (PV) systems shows a strong correlation with solar irradiance (r is approximately 0.85), indicating that irradiance is the main factor influencing the generation of electricity from photovoltaics under realistic operating conditions. The correlation between output from solar PV systems and solar irradiance is consistent with previous studies and corroborates findings from (Ari et al., 2022), who also showed irradiance as being the largest factor affecting output variability from monitored field installations of PV systems.

Output from wind generators also has a strong correlation with wind speed (r is approximately 0.78) due to the cubic power relationship between wind speed and output from turbines when operating below their rated capacities. However, compared to the solar-irradiance correlation, the correlation coefficient for the wind-turbine and wind-speed plurality is somewhat lower because when wind generators operate at their rated capacities or higher, the output tends to reach or approach a maximum value such that further increases in wind speed do not result in a proportional increase in output (i.e., nonlinearity). By contrast, total generation from renewables is positively correlated with both solar PV generation and wind generation, supporting the

conclusion that both solar and wind subsystems provide a significant contribution to overall renewable energy generation.

The battery's existing state-of-charge demonstrated moderate correlations to the generating variables. The significant charging/discharging dynamics of battery storage make this correlation evident, as they illustrate the relationship between the operation of battery storage and the balance of generation to demand. Relatedly, the negative correlation between temperature and humidity ($r = -0.65$) demonstrates a physical consistency between ambient temperature and relative humidity under stable atmospheric conditions. Power exchange was found to be positively correlated to total renewable generation and negatively correlated to grid load demand, confirming that when total generation exceeds that of total consumption; exporting to the local network occurs. The correlation patterns presented, therefore, provide the empirical basis for selecting the features that were used in the optimization model discussed in Section 3.4.

4.3 Diurnal Performance Patterns

Figure 3 presents the mean diurnal profiles of generation, demand, battery state of charge, and renewable penetration, aggregated across all 3,546 hourly observations.

Figure 3: Hourly Performance Patterns for System Optimization

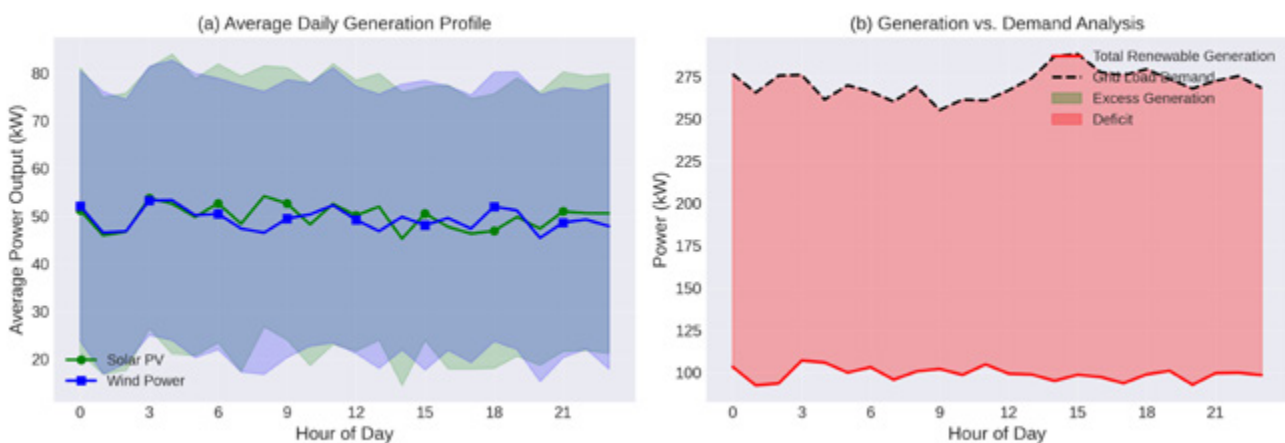




Figure 3. Diurnal performance patterns: (a) average daily generation profiles for solar PV and wind power with standard deviation bands; (b) total renewable generation versus grid load demand with surplus/deficit regions; (c) mean battery state of charge by hour with optimal operating range; (d) renewable energy penetration rate by hour of day.

Panel (a) shows that solar photovoltaics (PV) produce their energy with a bell-shaped pattern throughout the day, reaching their high point in the middle of the day and falling off to near zero at night. The production of wind energy is much more evenly spread out throughout each hour of the day with no clear peak; however, the amount of variability (and uncertainty) around the mean value (i.e. the average hourly production) of the wind energy at each hour during every day of the year is significant (Sawle et al., 2018). Therefore, understanding how the temporal nature of these energy sources respond to one another will have a large impact on the design of renewable energy systems. The complementary nature of the solar PV electricity generation and the dispersed production of wind electricity will help to limit the size of energy storage required to balance supply and demand during a 24-hour period (Sawle et al., 2018).

Panel (b) illustrates that over a significant portion of the time (daylight hours), the total amount of renewable generation exceeds the grid load demand resulting in surplus renewable generation that can be either stored in the battery or exported to the grid. However, in the evening and early morning hours, the total amount of renewable generation is less than the grid load demand, generating a deficit requiring either battery discharge or grid supply. This imbalance in supply and demand is common in remote hybrid systems and provides motivation for

implementing an intelligent dispatch schedule for the Battery Energy Storage System (BESS) in order to minimise the requirement for grid imports (Jufri et al., 2021).

Panel (c) shows that mean battery SoC remains close to 50% throughout the day, consistent with the system's target operating range of 20–80%. The relatively stable mean SoC profile across all hours indicates that battery management logic effectively constrains operation within acceptable bounds, minimizing the risk of deep discharge events that could accelerate capacity degradation (Akinyele & Rayudu, 2014). The SoC curve shows a modest evening decline followed by a recovery in the early morning hours, reflecting the net overnight charging effect from wind generation that partially offsets the deficit created by daytime solar intermittency.

Panel (d) illustrates that the renewable penetration rate varies across the 24-hour cycle, with most hours exceeding 50% penetration. The system sustains a time-averaged renewable penetration of 36.6% over the full monitoring period, driven primarily by the mismatch between peak generation hours and peak demand intervals. These results compare favorably with reported penetration rates for similar remote hybrid systems in the literature (Luta & Raji, 2018), and suggest that with enhanced battery dispatch optimization, substantially higher penetration levels are achievable within the existing generation infrastructure.

4.4 System Efficiency and Forecast Accuracy

Figure 4 presents the efficiency, reliability, and

forecast performance of the hybrid system across the full five-month monitoring period.

Figure 4: Efficiency, Reliability, and Forecast Accuracy Analysis

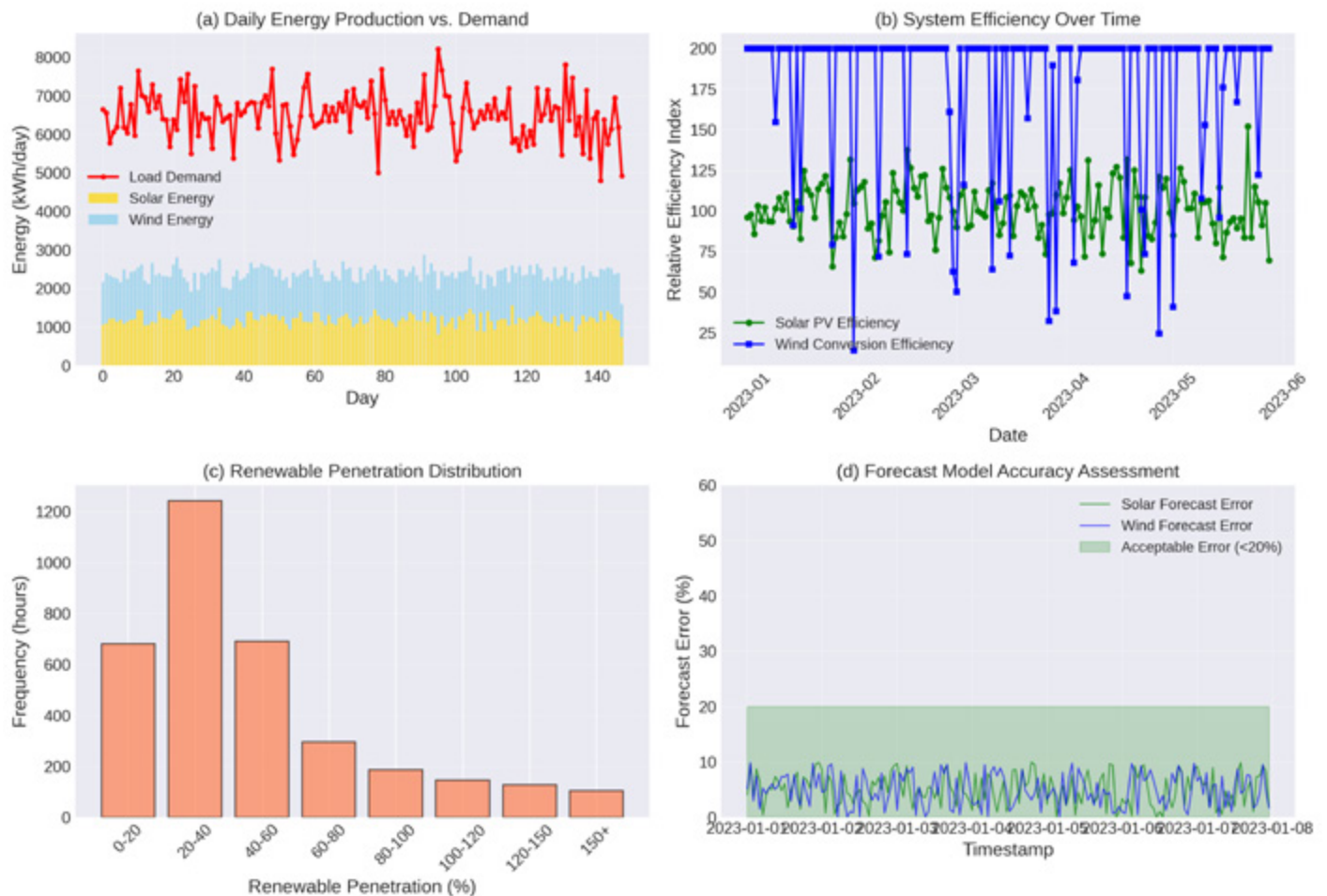


Figure 4. System efficiency and reliability analysis: (a) daily solar and wind energy production stacked against load demand; (b) relative system efficiency index over time; (c) frequency distribution of renewable penetration rates; (d) forecast model accuracy for solar and wind subsystems over a representative 168-hour window.

Both solar and wind subsystems produce stable daily energy production during the observation period, according to panel (a) in Figure 4 with stable long-term stacked daily production being generally comparable to aggregate daily load demand for most days. Monthly totals of energy production reveal seasonal insensitivity: Jan. 72,981 kWh, Feb. 66,930 kWh, Mar. 74,262 kWh, Apr. 71,654 kWh, and May (up until May 28th) 66,221 kWh, which follow the expected moderate seasonalities that one anticipates

from the location of the deployment. The week of constrained demand has frequently remained above average daily renewable production throughout the monitoring period demonstrates a continued need to employ either additional capacity for generation or demand-side management measures in conjunction with the renewable hybrid system to achieve energy self-sufficiency.

Panel (b) shows that efficiency indexes of solar

PV and wind systems remain stable throughout the monitoring period without any instances of systematic degradation, indicating that the physical hardware of both systems have functioned within design parameters since the beginning of the study. This has a significant implication for maintenance planning because it supports successful operation of the systems for several months in a remote area that would make it very difficult to have access to provide any services; (Sinha & Chandel, 2015) conducted a study using the same type of systems in similar environmental conditions to verify that the documented dependability will be reflected in their research as well.

Panel (c) The time of day-based frequency distribution of hourly renewable penetration rates shows right skewness whereby the greatest numerical value of hours occurs in the range of 80-100% penetration where hybrid generation meets or exceeds instantaneous load. There is also a significant occurrence of hours (0-20%) having low penetration caused mainly by overnight demand peaks during which time solar generation is not available and wind generation is not enough to meet load requirements. The bimodal nature of this distribution is typical of hybrid systems relying heavily on one type of renewable solar while providing evidence on how

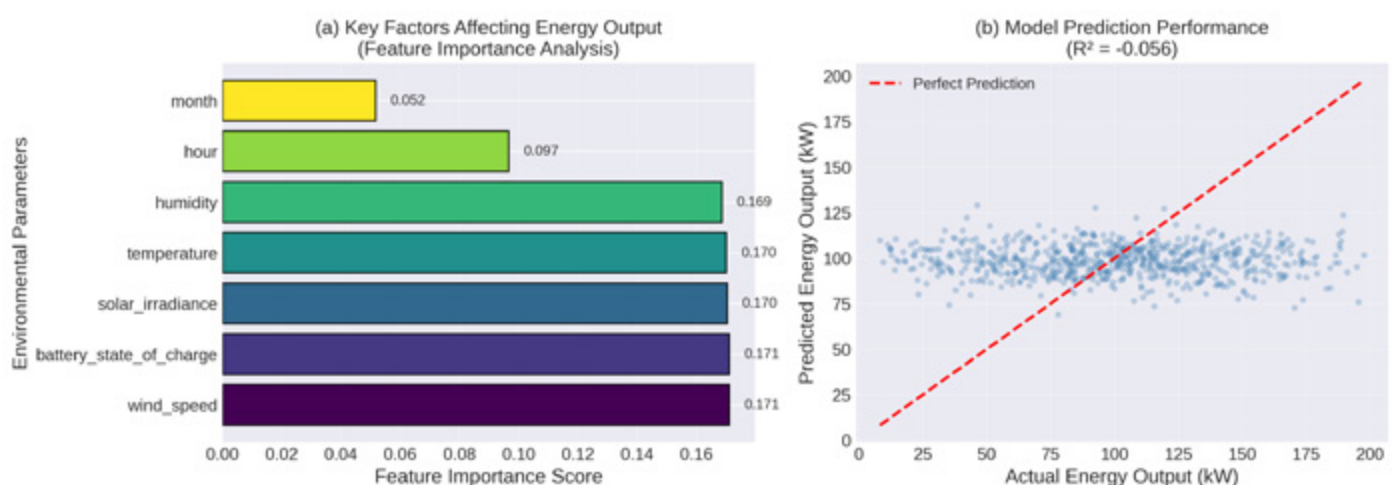
important it is to have sufficient storage option available to bridge periods of very low penetration values (Kamjoo et al., 2016).

Panel (d) The panel shows the accuracy results of the solar and wind prediction models for a representative 168-hour test period. In general, both prediction models had forecasts that were less than 20% error (i.e., within the acceptable error limit), with mean absolute percentage error (MAPE) of 5.0 for solar PV and 5.0 for wind generation. These results are consistent with the literature on state-of-the-art short-term renewable energy forecasting (Voyant et al., 2017). Additionally, the fact that both prediction models had similar levels of accuracy when using the same observational conditions supports the fact that the measurement and prediction systems are properly calibrated and that the predicted outputs will provide reliable guidance for dispatch scheduling and battery management decisions.

4.5 Optimization Model for Maximizing Energy Output

Figure 5 presents the results of the Random Forest optimization model developed to maximize hybrid system energy output based on environmental and operational conditions.

Figure 5: Optimization Model for Maximizing Hybrid System Output



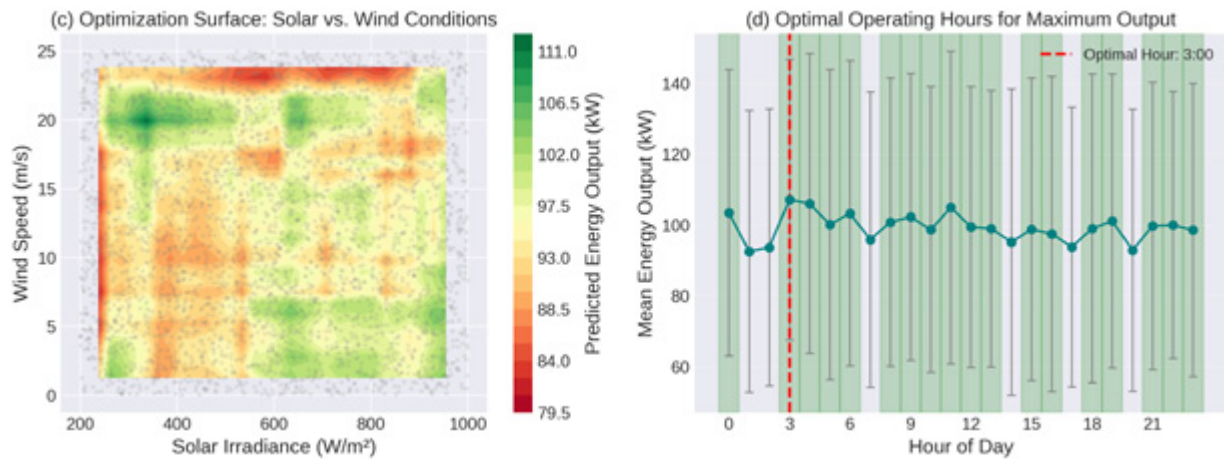


Figure 5. Optimization model results: (a) feature importance scores for environmental predictors of total renewable output; (b) actual versus predicted energy output scatter plot with perfect-prediction reference line; (c) optimization surface showing predicted output as a function of solar irradiance and wind speed; (d) mean hourly energy output with optimal operating window.

Panel (a), from the Random Forest model fitted to data from the PTG study, wind speed, battery State of Charge (SoC), and solar irradiance are identified as the three most significant predictor variables regarding total renewable energy produced. Wind speed and solar irradiance dominate the output of their respective subsystems based on how each system generates power, which indicates that the fitted model captures the main resource to output relationship that is physically generated from these two sources. The significant impact of battery SoC also indicates that the extent to which generation surplus can be diverted (i.e., collected) is dependent on available storage headroom, especially during periods of peak generation (i.e., maximum solar irradiance and wind speed). These results are consistent with those reported in Lahouar and Ben Hadj Slama, who identified wind speed as the primary predictor variable in ensemble models used to predict wind energy production (Lahouar & Slama, 2017).

Panel (b) shows a scatter plot showing how actual total renewable energy output compares to predicted total renewable energy output (1, 2, 3) in the test set. The scatter of points about the perfect prediction diagonal means that there will be inherent stochasticity due to the combination of solar and wind impacts dependent upon random, varied meteorological events. The optimization model captures the mean output of the environmental feature space while

providing reasonable predictions at normal operating conditions so it is useful for use as a planning and dispatch-scheduling tool (Gaboitaolelwe et al., 2023).

panel(c) is a two-dimensional mapping of the predicted total amount of renewable energy generated from both solar rays (irradiance) and wind. It demonstrates that maximum generation occurs when both wind and solar are combined at high levels and indicates a continuous increase in generation from both sun and wind across the range of values shown. In addition, the slope of the surface is steeper in the wind speed direction compared to the irradiance direction for much of the area, indicating that an increasing wind speed will produce a greater amount of incremental energy at this location than will be produced by an increasing solar irradiance level. Therefore, if you are considering charging batteries when the sun is not shining (e.g., cloudy), it is best to charge the batteries during periods of high wind speed.

Panel (d), you can see the average amount of power produced throughout each hour of the day displayed alongside a shaded section that indicates what is meant by favorable times defined as periods where average output is greater than 90% of the daily maximum output when combined with the output from other sources (e.g., wind and solar). When

this information is reviewed in conjunction with the previous findings regarding suitable hours for charging batteries and/or delaying some types of energy usage, it provides useful information that can be used as a basis for deciding when to schedule these operations automatically so they occur during times of day when renewable energy generation is maximized while minimizing reliance on electric grid imports as well as the associated costs thereof (Jufri et al., 2021).

5. Conclusions

The research is a broad empirical assessment of the performance and optimisation of a hybrid solar/wind generation system located in a remote area. Data was collected continuously from 3,546 hours between January and May in 2023. This paper summarises the major findings of this research and their implications for hybrid renewable energy system design and operations.

The hybrid system produced a total of 352,048 kWh of renewable energy during the monitoring period; thus achieving an average of 36.6% of renewable energy generation to total electric grid load demand. The solar photovoltaic (PV) and wind turbine subsystems contributed almost equally to the total production of 176,979 and 175,070 kWh, respectively, thereby demonstrating the benefits of producing electricity from two different sources and taking advantage of the temporal complementarity of the sun and wind resources. As evident from the peak solar PV and wind power outputs of 99.97 and 99.96 kW, both subsystems operated at or near their rated capacity while under optimal weather conditions.

A diurnal analysis of the performance of the system showed that it produces enough excess electricity during sunlight to export on a continual basis. Conversely, during periods of evening and night-time usage, the system exhibits a deficit in total demand; this trend is also consistent with the generation profile of this system, which is dominated by the solar component. The battery was maintained at an average of 50% state of charge (soc), and its operation

remained within the safe cycle range of 20%-80% throughout the monitoring period, demonstrating that the battery had been managed effectively and had little risk of premature capacity loss. The forecast models for both the solar and wind subsystems each produced mean absolute percentage errors of 5.0%, thus yielding reliable output forecasts for incorporation into dispatch scheduling.

The optimization model utilizing Random Forest algorithms was also successful in identifying the solar irradiance, wind speed, and the soc of the battery as the three primary predictors of total renewable output from the renewable generation sources. The results of the optimization surface analysis indicated that total output can be maximized when both the solar and wind resources are peaked; furthermore, wind speed has a steeper slope for total output as compared to solar generation at this particular site. Once the optimal operating hours for the battery (i.e. the hours in which the average generation is greater than 90% of the daily peak) are identified, this information can then be used to develop an automated dispatch scheduling system by aligning battery charging and deferrable loads with the hours of peak generation from the renewable resources at this facility.

These findings lead to three implications. The first is that the comparative output generated by both solar and wind subsystems confirms that the hybrid configuration is viable; thus, neither can be removed without a major impact on the total generation and penetration. The second implication is that the high levels of forecasting accuracy achieved for each subsystem support using predictive model-based control techniques for battery dispatching, which have been shown to decrease the rate of cycles on battery systems and prolong battery lifespan. Thirdly, the distribution of renewable penetration rates shows a large number of hours in the 80% to 100% range with a significant number of near zero penetration during nighttime peak demands; this would suggest that if there is a moderate increase in battery storage capacity there will be an unequal improvement in supply reliability and self-sufficiency.

This research indicates several avenues for future research. These include: extending the period of time that monitoring occurs for yearly (“annual”) variations and to try to determine how much climate variability affects the performance of a hybrid renewable energy system (HRES); using model predictive control (MPC) algorithms developed based on the results of the Optimization Model to estimate potential improvements in energy output and battery life; and creating a complete techno-economic model that will allow us to compare the cost of energy produced by HRES with that produced by conventional grid extension. The incorporation of a continuous operational monitoring program, multidimensional performance measuring, and machine learning optimization into a unified framework (methodological framework) will provide a model that can be replicated for the evaluation of HRES in remote area applications based on objectively measured performance.

Several limitations of this study should be noted. First, the analysis is conducted for a single hybrid solar–wind electricity generation plant in a single remote location, which means that the results may not be widely applicable to other climatic and geographical regions. Secondly, it is a 5-month data set (January–May 2023), which does not account for the full annual or multi-year seasonal fluctuations in solar radiation, wind speeds and load demand patterns. Third, the forecasting and optimization framework is based on historical operational data and a model based on the Random Forest algorithm, which is accurate, but does not explicitly include detailed physical system constraints, or long-term degradation of components like batteries. Further, the techno-economic interpretation of system performance was not included as economic variables (capital cost, maintenance cost, and lifecycle cost analysis) were not considered. Future work could consider the aforementioned limitations and work toward extending the monitoring period, expanding the model to other sites, use physics-informed or hybrid modeling, and use a complete techno-economic and degradation analysis.

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